

# *Application of Artificial Intelligence-Driven Personalized Learning Path Planning in Mechanical Engineering Education*

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**Abstract:** With the rapid development of artificial intelligence (AI) technology, mechanical engineering education is facing a historic opportunity to transform from a standardized training model to a personalized learning paradigm. This paper systematically explores the application value and technical framework of AI-driven personalized learning path planning in the teaching of mechanical engineering majors. First, the study analyzes the characteristics of the knowledge system of mechanical engineering and the diversity of students' learning needs and then constructs a personalized learning path planning model integrating knowledge graph, learning analytics, and intelligent recommendation as a trinity. The paper elaborates on the implementation mechanisms of core modules such as learner model construction, knowledge state diagnosis, and dynamic path optimization, and discusses the specific application scenarios of personalized learning paths in theoretical teaching, virtual simulation, and practical links in combination with the curriculum system of mechanical engineering majors. Finally, the study probes into the transformation path of teachers' roles under the background of human-machine collaboration and the ethical boundaries faced by technological application. This paper aims to provide theoretical reference and practical guidance for mechanical engineering educators to understand and apply AI technology, realize teaching students in accordance with their aptitudes, and improve the quality of talent cultivation.

## 1. Introduction

### 1.1. Research Background and Problem Proposal

As a typical representative of traditional engineering majors, mechanical engineering features a knowledge system with remarkable hierarchy and systematicness. From basic mechanics and mechanical principles to professional design and manufacturing technology, there is a rigorous logical progressive relationship among various courses. This characteristic determines that the learning process of mechanical engineering students has such features as strong path dependence,

high cognitive load, and the interweaving of theory and practice [1]. However, the current mechanical engineering majors in universities generally adopt a standardized teaching model of "unified syllabus, unified progress, and unified assessment", which makes it difficult to take into account the significant individual differences of students in knowledge foundation, cognitive style, learning rhythm, and other aspects.

The rapid development of AI technology provides a new possibility to solve this dilemma. Intelligent tutoring systems, adaptive learning platforms, learning analytics technology, and other tools have shown great potential in the field of education [2, 3]. Studies have shown that AI-driven personalized learning platforms can improve students' academic performance by up to 25% and significantly enhance learning engagement [2]. For mechanical engineering education, how to use AI technology to dynamically plan the optimal learning path for students based on their learning behavior data and knowledge mastery status and realize the transformation from a "one-size-fits-all" approach to "teaching students in accordance with their aptitudes" has become a core issue that needs in-depth research urgently.

## 1.2. Connotation and Value of Personalized Learning Path Planning

Personalized learning path planning refers to the process in which the system automatically generates and dynamically adjusts the sequence of learning content according to the learner's knowledge foundation, learning objectives, cognitive characteristics, and behavioral performance [3]. In the context of mechanical engineering education, this process has three core values: first, helping students establish a clear learning map in the huge knowledge system and avoiding cognitive disorientation; second, accurately pushing learning resources for students' knowledge weaknesses to improve learning efficiency; third, cultivating students' ability of independent learning planning and regulation through continuous optimization of learning paths, laying a foundation for their lifelong learning [4].

## 1.3. Analysis of Domestic and Foreign Research Status

At present, research on the application of AI in engineering education has formed several hot directions. Alghazo et al. systematically sorted out the application of AI in mechanical engineering education from 2018 to 2023 and identified key fields such as personalized learning, intelligent tutoring systems, digitization of engineering drawings, and simulation and evaluation enhancement [5]. A systematic review by Hallmark et al. further pointed out that AI-driven virtual simulation tools such as the Mars Exploration Control Laboratory can improve student engagement by 30% and conceptual understanding by 20% [6]. In terms of intelligent tutoring systems, Becker et al. developed a knowledge-based intelligent tutoring system for engineering design education, realizing personalized guidance and feedback on the design process [1]. Domestic universities are also actively exploring this field: the course *Additive Manufacturing Processes and Equipment* at Beihang University has constructed a five-level knowledge system graph and customized learning paths for students with different professional backgrounds combined with a set of personalized auxiliary instructions. Tianjin University of Technology has built a teaching paradigm of "accurate diagnosis-intelligent generation-personalized guidance" in the course *Engineering Drawing*, relying on a multi-modal learning situation analysis platform.

However, existing studies mostly focus on the application of a single technology or a single course and lack a systematic discussion on the learning path planning system for the overall knowledge system of mechanical engineering majors. This paper aims to make up for this deficiency and construct a systematic theoretical framework and practical path.

## 2. Theoretical Basis and Technical Framework of Personalized Learning Path Planning

### 2.1. Core Theoretical Basis

The theoretical foundation of personalized learning path planning can be traced back to a number of classic educational theories and learning science achievements. Vygotsky's "zone of proximal development" theory emphasizes that teaching should focus on students' potential development level, and students should complete tasks beyond their independent abilities with appropriate support [3]. This idea provides a theoretical basis for dynamically adjusting the difficulty of learning tasks. Cognitive load theory reveals the influence of the presentation mode of learning content on the allocation of cognitive resources, suggesting that learning path planning needs to consider the sequence and complexity of knowledge presentation. Bloom's mastery learning theory points out that as long as sufficient time and appropriate teaching conditions are provided, the vast majority of students can master the learning content, which provides belief support for the effectiveness of personalized learning [1].

### 2.2. Classic Architecture of Intelligent Tutoring Systems

The classic architecture of an intelligent tutoring system consists of four core modules: the expert model, the learner model, the tutoring model, and the user interface [1, 3]. The expert model encapsulates the professional knowledge of the field to be taught and serves as a standard reference for evaluating learners' performance; the learner model dynamically records and infers learners' knowledge state, cognitive preferences, and learning progress; the tutoring model decides "what to teach" and "how to teach" based on the diagnostic information output by the learner model, including content selection, sequence arrangement, feedback generation, and so on; and the user interface undertakes the interactive function between the system and the learner. This architecture provides a basic blueprint for the design of a personalized learning path planning system.

### 2.3. Three-Dimensional Technical Framework of Personalized Learning Path Planning

Based on the above theoretical basis, this paper constructs a three-dimensional technical framework for personalized learning path planning integrating knowledge graph construction, learning analytics and diagnosis, and intelligent recommendation and decision-making, as shown in Figure 1.

Knowledge graph construction is the knowledge foundation of path planning. The professional knowledge system of mechanical engineering can be abstracted into a knowledge graph containing concept nodes and relational edges, where nodes represent knowledge points (e.g., "gear module," "bending stress") and edges represent prerequisite, associative, or inclusive relationships between knowledge points.

Learning analytics and diagnosis is the perception system of path planning. By collecting and analyzing the behavioral data generated by learners in online learning platforms, virtual simulation experiments, homework and quizzes, and other scenarios, the system can real-time infer learners' knowledge mastery, learning strategy preferences, cognitive engagement level, and other characteristics.

Intelligent recommendation and decision-making are the core engine of path planning. Based on the gap between the learner's current knowledge state and the target state, the system uses machine learning algorithms (such as reinforcement learning, collaborative filtering, sequence pattern mining, etc.) to dynamically generate the optimal learning path. Path optimization is guided by multi-objective functions such as learning efficiency, knowledge mastery, and learning engagement, and

it conducts search and decision-making in the knowledge graph space. A systematic review in *IEEE Access* points out that this process needs to balance personalization on the student side and interpretability on the teacher side [3].

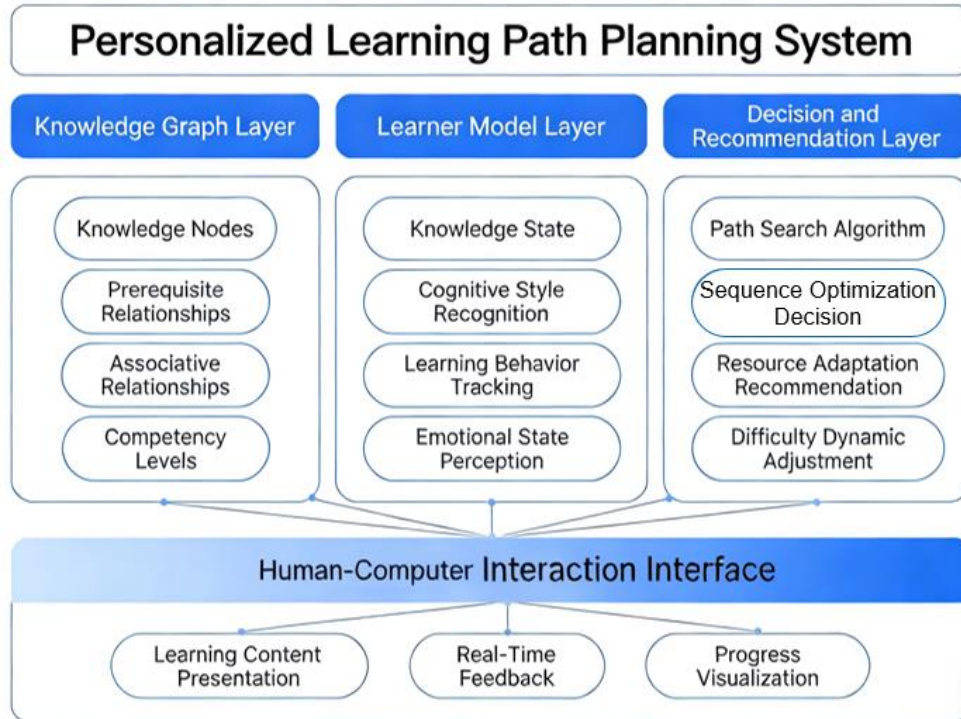


Figure 1: Technical framework of AI-driven personalized learning path planning.

### 3. Core Modules of Personalized Learning Path Planning for Mechanical Engineering Majors

#### 3.1. Learner Model Construction

The learner model is the starting point of personalized learning path planning, and its core task is to transform the implicit learner characteristics into computable formal representations. In the context of mechanical engineering education, the learner model needs to cover multi-dimensional information.

The knowledge state dimension depicts the learner's mastery of each knowledge point. Common modeling methods include knowledge tracing models and Bayesian networks [3]. For example, in the course *Mechanical Principles*, the system can track the probability of students mastering knowledge points such as "degree of freedom calculation" and "institutional motion analysis" to form a knowledge mastery matrix.

The cognitive style dimension describes the learner's preferences in information processing methods. According to the Felder-Silverman Learning Style Model, learners can be divided into active/reflective, sensing/intuitive, visual/verbal, and sequential/global types [3]. For students who prefer a visual learning style, the system can prioritize pushing 3D animation, engineering diagrams, and other types of resources; for students who prefer a sequential learning style, the content is presented in strict accordance with the logical progression of knowledge.

The behavioral pattern dimension captures the operation sequences and strategy choices of learners in the learning process. For example, in CAD modeling practice, the system can analyze whether students adopt a systematic structured strategy of "overall planning first and then refinement" or an exploratory strategy of "high-frequency trial-and-error iteration" [4].

### 3.2. Knowledge State Diagnosis and Weak Point Identification

Accurate diagnosis of knowledge state is a prerequisite for personalized path planning. The diagnosis process is usually divided into two levels: formative diagnosis and summative diagnosis. Formative diagnosis occurs during the learning process and in real-time infers the learner's understanding level by analyzing their exercise responses, problem-solving trajectories, virtual experiment operation sequences, and other data [1]. For example, in the course *Mechanical Design*, when students carry out shafting design practice, the system can diagnose their mastery of shafting design rules according to their design decisions, such as bearing type selection, shaft shoulder height, and fit tolerance.

Weak point identification is to locate the root cause of learning obstacles on the basis of diagnosis. The prerequisite relationship in the knowledge graph provides a reasoning path for this process: if a student performs poorly in "gear strength calculation," the system can trace back to their mastery of prerequisite knowledge points such as "material mechanics" and "stress analysis" and judge whether the weak root cause is the understanding of the current knowledge point itself or the poor foundation of prerequisite knowledge.

### 3.3. Dynamic Path Planning Algorithms

Based on the diagnosis results and the knowledge graph, the system needs to dynamically plan the subsequent learning path. This process can be formalized as a problem of searching for the optimal sequence from the current knowledge state to the target knowledge state in the knowledge graph space.

Reinforcement learning is an effective way to realize path planning optimization [3]. The learning path planning is modeled as a Markov Decision Process: the state is the learner's knowledge mastery vector, the action is the recommended learning activity (e.g., watching videos, completing exercises, conducting simulation experiments), and the reward function comprehensively considers indicators such as learning effect, time consumption, and difficulty matching degree. The agent continuously optimizes the strategy through trial and error in the interaction with learners and finally learns to recommend the optimal learning sequence for different types of students.

Sequence pattern mining extracts typical path patterns of successful learners from historical learning data [2]. By analyzing the learning trajectories of outstanding students in previous sessions, effective path patterns such as "theoretical learning→virtual simulation→practical operation" or "case introduction→principal exploration→application expansion" are found to provide references for current learners.

### 3.4. Learning Resource Adaptation and Feedback Generation

The final output of path planning needs to be implemented into specific learning resources and feedback guidance. Resource adaptation includes content difficulty matching, presentation form selection, exercise task generation, and other aspects. For students with weak mastery of knowledge points, the system recommends basic explanation resources and simple application exercises; for students who have basically mastered the knowledge points, it pushes comprehensive application tasks and engineering case expansion resources.

Instant feedback generation is a key link to promote in-depth learning. Intelligent tutoring systems can provide real-time prompts, error diagnosis, step guidance, and other feedback during the student's problem-solving process. For example, if a student makes a mistake in conducting institutional motion simulation, the system not only points out that "the result is inconsistent with

the expectation," but also locates the specific reasons, such as "the rod length condition is not satisfied" and "the drive setting is wrong," and guides them to consult relevant knowledge. Table 1 summarizes the AI-based personalized learning paths for mechanical engineering majors.

Table 1: Corresponding relationship between AI personalized learning function modules and mechanical engineering teaching scenarios.

AI Function Modules	Typical Application Scenarios in Mechanical Engineering	Teaching Support Value
Knowledge state diagnosis	Homework correction and error cause analysis in <i>Engineering Graphics</i> .	Accurately identify defects in drawing specifications and shortcomings in spatial imagination ability.
Personalized path recommendation	Learning sequence arrangement in <i>Mechanical Principles</i> .	Dynamically adjust the learning order of institutional analysis and design according to the prerequisite foundation.
Real-time feedback guidance	CAD/CAE software operation and modeling practice.	Instantly correct modeling errors and guide parameter optimization and design improvement.
Adaptive simulation experiments	Virtual mechanics laboratory, institutional motion simulation.	Dynamically adjust experimental parameters and task difficulty according to students' mastery level.
Learning situation analysis and warning	Full-cycle learning behavior tracking and intervention.	Predict academic risks and timely push early warning and remedial learning resources.

## 4. Application of Personalized Learning Paths in Multiple Scenarios for Mechanical Engineering Majors

### 4.1. Path Planning in Theoretical Course Learning

Mechanical engineering theoretical courses (such as *Theoretical Mechanics*, *Mechanical Principles*, and *Mechanical Design*) are characterized by abstract concepts, rigorous logic, and numerous formulas. Students' learning difficulties in these courses often stem from the lack of prerequisite knowledge, differences in abstract thinking ability, or maladaptation to learning rhythm.

Personalized learning path planning can realize a closed loop of "prerequisite diagnosis - dynamic adjustment - accurate recommendation" at the course level. At the beginning of the course, the system diagnoses students' mastery of prerequisite knowledge through a pre-test and pushes preparatory learning content for students with weak foundations. During the course, the system tracks the learning effect of each knowledge point and dynamically adjusts the depth and breadth of subsequent content. For example, in the course *Mechanical Design*, if a student performs excellently in the "gear transmission" unit, the system can recommend advanced content such as "modified gear design" or "gear profile modification"; if the student performs poorly, the system will guide them to review the basics such as "meshing principle" and "strength calculation" and provide more practice opportunities.

### 4.2. Path Adaptation in Virtual Simulation and Practical Links

The application of virtual simulation experiments and remote laboratories in mechanical engineering education is becoming increasingly widespread. Practice at the Hong Kong University of Science and Technology shows that the teaching environment integrating Augmented Reality (AR) and AI enables students to familiarize themselves with equipment operation and experimental procedures in a virtual environment before conducting physical experiments, which significantly

improves learning effects and safety [4].

In the virtual simulation environment, personalized path planning is manifested in the form of progressive experimental task difficulty, expanded parameter exploration space, dynamic adjustment of guidance prompts, and so on. Taking the virtual wind tunnel experiment of *Fluid Mechanics* as an example, junior students can complete the aerodynamic parameter measurement of standard airfoils according to the guided steps; advanced students can independently explore the influence of different airfoils, angles of attack, and incoming flow velocities on lift and drag characteristics; senior students can even attempt airfoil optimization design, and the system provides real-time optimization suggestions according to their operations.

### **4.3. Path Support in Project-Based Learning and Graduation Design**

Project-based learning and graduation design are key links for mechanical engineering majors to cultivate students' comprehensive engineering capabilities. Such open-ended problem-solving processes are complex with diverse paths, and students are prone to the predicament of "not knowing where to start" and "being stuck in a certain link and unable to proceed."

Personalized learning path planning plays a dual role of "process guidance" and "resource support" in such scenarios. According to the project type and current progress, the system recommends corresponding resources such as design methods, analysis tools, and reference cases. When detecting those students staying in a certain link (such as scheme selection or strength check) for too long or showing signs of confusion, it actively pushes targeted prompts or invites teachers to intervene. The Augmentor framework proposed by Norwegian scholars has made a useful exploration in this regard. Through a human-machine collaboration mechanism, the framework enables the system to learn the decision-making mode of expert operators and provide decision support at the right time [7].

## **5. Human-Machine Collaboration and the Transformation of Teachers' Roles**

### **5.1. Role Evolution from Knowledge Transmitter to Learning Designer**

AI-driven personalized learning path planning is not intended to replace teachers but to promote the transformation of teachers' roles to a higher level. In the new teaching paradigm, teachers' roles change from knowledge transmitters to learning designers, growth mentors, and meaning makers. Teachers are responsible for designing the structure and boundaries of the course knowledge graph, setting the macro goals and ethical constraints of learning path planning, and reviewing and optimizing the personalized schemes recommended by the system. More importantly, teachers undertake the functions that the system finds difficult to perform: stimulating learning motivation, cultivating engineering ethics, guiding critical thinking, passing on industry experience, and so on.

### **5.2. Cultivation of Teachers' Data Literacy and AI Collaboration Competence**

The effective application of personalized learning path planning systems requires teachers to have corresponding data literacy and AI collaboration competence. Teachers need to understand the meaning of learning analytics reports and adjust teaching strategies based on data insights; master the methods of interacting with intelligent systems and make professional judgments and revisions on system recommendations; and more importantly, have critical thinking to identify possible biases and limitations of algorithms. A review by Hallmark et al. points out that targeted teacher training can improve teachers' confidence in integrating AI tools by 40% [6].

### **5.3. Design of Human-Machine Collaborative Decision-Making Mechanism**

An ideal personalized learning path planning system should be designed as a human-machine collaborative decision-making model rather than complete algorithm automation. The recommendations of the system should maintain interpretability, showing the basis for path selection to teachers and students; teachers have the right to review and revise the system's decisions and can adjust the recommended schemes according to their in-depth understanding of students; students should also be given an appropriate right of choice to cultivate their metacognition and autonomous learning ability. This "bidirectional human-machine adaptation" collaborative mechanism can give play to the advantages of AI in data processing while ensuring the humanistic temperature and professional judgment of education.

## **6. Challenges and Ethical Considerations**

### **6.1. Technical Challenges**

The large-scale application of personalized learning path planning in mechanical engineering education still faces multiple technical challenges. First, the completeness and accuracy of the knowledge graph cannot be achieved overnight, and it requires continuous participation and maintenance of domain experts. Second, the generalization ability of the learner model is limited, and the cross-course and cross-grade transfer of student models is not yet mature. Third, the interpretability of algorithm decision-making is insufficient, and teachers and students find it difficult to understand the logic behind the recommendations, which affects trust and adoption intention. Fourth, the stability and compatibility of hardware and software systems may affect the user experience and learning continuity.

### **6.2. Data Privacy and Algorithmic Ethics**

The collection and analysis of learning behavior data involve the core issue of student privacy protection. How to balance data utility and privacy protection is a problem that must be prioritized in system design. Algorithmic bias is also worthy of vigilance: biases in training data may lead the system to have an adverse impact on students with specific learning styles, cognitive levels, or backgrounds, exacerbating rather than alleviating educational inequality. In addition, over-reliance on system recommendations may weaken students' autonomous learning ability and form a negative effect of "path dependence."

### **6.3. Balance between Technological Application and the Essence of Education**

While embracing AI technology, we must clearly recognize the fundamental principle that technology serves the essence of education. The value of personalized learning path planning lies in supporting rather than replacing students' active learning and enhancing rather than weakening the in-depth interaction between teachers and students. The goal of mechanical engineering education is not only the transmission of knowledge and the mastery of skills but also the cultivation of engineering thinking, innovative ability, and professional literacy. The cultivation of these higher-order abilities is inseparable from exploration in real problem situations, reflection on failure, collision in team collaboration, and the influence of teachers' words and deeds. Therefore, the design and application of personalized learning path planning systems should aim to expand rather than limit learning possibilities and seek a dynamic balance between technological empowerment and humanistic care.

## 7. Conclusions and Prospects

This paper systematically discusses the application value, technical framework, and practical path of AI-driven personalized learning path planning in mechanical engineering education. The study shows that the three-dimensional technical framework integrating knowledge graph, learning analytics, and intelligent recommendation can effectively support the personalized learning of mechanical engineering students in multiple scenarios such as theoretical courses, virtual simulation, and project practice. The coordinated operation of core modules such as learner model construction, knowledge state diagnosis, dynamic path planning, and resource adaptation feedback provides technical possibilities for realizing the educational ideal of teaching students in accordance with their aptitudes.

Looking to the future, personalized learning path planning technology will show several development trends. Multimodal learning analytics technology will integrate multi-source data such as voice, facial expressions, and eye movements to achieve a more refined perception of students' cognitive and emotional states. The application of generative AI will make the links of learning resource generation, feedback dialogue, and problem design more flexible and adaptive. The development of explainable AI technology will enhance the transparency of algorithm decision-making and improve teachers' and students' trust in the system. More importantly, personalized learning path planning will go beyond the scope of a single course, extend to professional training programs, interdisciplinary learning, and even lifelong learning fields, and build a personalized learning support system that runs through the entire academic career and even professional career of students.

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